Forecasting oil prices

Stavros Degiannakis and George Filis

Panteion University of Social and Political Sciences, Panteion University of Social and Political Sciences

14 March 2017

Forecasting oil prices

Stavros Degiannakis[1,2] and George Filis[1,*]

[1]Department of Economics and Regional Development, Panteion University of Social and Political Sciences, 136 Syggrou Avenue, 17671, Greece.
[2]Postgraduate Department of Business Administration, Hellenic Open University, Aristotelous 18, 26 335, Greece.

*Corresponding author's email: gfilis@panteion.gr

PLEASE DO NOT USE WITHOUT PERMISSION

Abstract

Accurate and economically useful oil price forecasts have gained significant importance over the last decade. The majority of the studies use information from the oil market fundamentals to generate oil price forecasts. Nevertheless, the extant literature has convincingly shown that oil prices are nowadays interconnected with the financial and commodities markets. Despite this, there is scarce evidence as to whether information from asset markets could improve the forecasting accuracy of oil prices. Even more, there is limited knowledge whether ultra-high frequency data, given their rich information, could improve monthly oil price forecasts. This paper fills this void, using oil market fundamentals, as well as, daily returns and volatilities based on ultra-high frequency data from financial and commodities assets, in forecasting monthly oil prices up to 12-months ahead. Our findings show that asset volatilities significantly improve oil price forecasts relatively to the no-change forecast, as well as, relatively to the well-established models of the literature, although this does not hold for asset returns. These results hold true even when we consider turbulent oil market conditions, as well as, forecast combinations.

Keywords: Oil price forecasting, Brent crude oil, intra-day data, MIDAS.

JEL: C53, G14, G15, Q43, Q47

1. Introduction

The importance of oil price forecasting has been long established in the extant literature, as well as, in the economic press and policy documents. For instance, the IMF (2016) maintains that the recent falling oil prices create significant deflationary pressures (especially for the oil-importing economies), imposing further constraints to central banks to support growth, given that many countries currently operate in a low interest rate environment. Even more, at the same report the IMF (2016) concludes that "A protracted period of low oil prices could further destabilize the outlook for oil-exporting countries" (p. XVI). ECB (2016), on the other hand, maintains that "the fiscal situation has become increasingly more challenging in several major oil producers, particularly those with currency pegs to the US dollar…", given that "crude oil prices falling well below fiscal breakeven prices…" (p. 2).

The media also provide anecdotal evidence on the macroeconomic effects of the recent oil price fluctuations. Barnato (2016), for example, links oil price fluctuations with the quantitative easing in EMU, arguing that "Given the recent oil price rise, a key question is to what extent the ECB will raise its inflation projections for 2016-2018 and what this might signal for its QE (quantitative easing) policy after March 2017." Similarly, Blas and Kennedy (2016) highlight the concern that the declining energy prices might push the world economy "into a tailspin".

Overall, the importance of oil price forecasts stems from the fact that they are essential for stakeholders, such as oil-intensive industries, investors, financial corporations and risk managers, but also for regulators and central banks, in order to measure financial and economic stability (Elder and Serletis, 2010). Thus, accurate and economically useful oil price forecasts have gained significant importance over the last decade.

Nevertheless, the literature maintains that oil price forecasting could be a difficult exercise, due to the fact that oil prices exhibit heterogeneous patterns over time as at different times they are influenced by different (fundamental) factors (i.e. demand or supply of oil, oil inventories, etc.).

For instance, according to Hamilton (2009a,b) there are periods when the oil prices are pushed to higher levels due to major oil production disruptions, which were not accommodated by a similar reduction in oil demand (e.g. during the Yom Kippur War in 1973, the Iranian revolution in 1978 or the Arab Spring in 2010). On the other hand, Kilian (2009) maintains that increased precautionary oil demand due to uncertainty for the future availability of oil leads to higher oil prices. According to Kilian (2009), the aforementioned uncertainty increases when geopolitical uncertainty is high (particularly in the Middle-East region).

Even more, the remarkable growth of several emerging economies, and more prominently this of the Chinese economy, from 2004 to 2007 significantly increased the oil demand from these countries, while the oil supply did not follow suit, driving oil prices at unprecedented levels (Hamilton, 2009a,b, Kilian, 2009). Equivalently, the global economic recession during the Global Financial Crisis of 2007-09 led to the collapse of the oil prices, as the dramatic reduction of oil demand was not accompanied by a reduction in the supply of oil.

Other authors also maintain that most of the largest oil price fluctuations since the early 70s, reflect changes in oil demand (see, for instance, see, e.g., Barsky and Kilian 2004; Kilian and Murphy 2012, 2014; Lippi and Nobili 2012; Baumeister and Peersman 2013; Kilian and Hicks 2013; Kilian and Lee 2014).

Despite the fact that oil market fundamentals have triggered oil price swings, a recent strand in the literature maintains that the crude oil market has experienced an increased financialisation since the early 2000 (see, for instance, Büyüksahin and Robe, 2014; Silvennoinen and Thorp, 2013; Fattouh *et al.*, 2013; Tang and Xiong, 2012), which has created tighter links between the financial and the oil markets. In particular, Fattouh *et al.* (2013) argue that the financialisation of the oil market, as this is documented by the increased participation of hedge funds, pension funds and insurance companies in the market, has led to its increased comovements with the financial markets, as well as, other energy-related and non-energy related commodities. Akram (2009) also maintains that the financialisation of the oil market is evident due to the increased correlation between oil and foreign exchange returns. Thus, apart from the fundamentals that could drive oil prices, financial and commodity markets are expected to impact oil price fluctuations and thus provide useful information for oil price forecasts.

As we explain in Section 2, typical efforts to forecast the price of oil include time-series and structural models, as well as, the no-change forecasts. Furthermore, the vast majority of the existing literature uses low frequency data (monthly or quarterly) to forecast monthly or quarterly oil prices, based on oil market fundamentals.

Against this backdrop the aim of this study is twofold. First, we develop a forecasting framework that takes into consideration the different channels that provide predictable information to oil prices (i.e. fundamentals, financials, commodities, etc.). Second, we utilise ultra-high frequency data (tick-by-tick) to forecast monthly oil prices.

To do so, we employ a MIDAS framework, using tick-by-tick financial and commodities data, which complement the set of the established oil market fundamental variables. Several studies have provided evidence that the MIDAS framework has the ability to improve the forecasting accuracy for low-frequency data, using information from higher-frequency predictors (see, for instance, Andreou *et al.*, 2013; Clements and Galvao, 2008, 2009; Ghysels and Wright, 2009; Hamilton, 2008). Needless to mention that in order to allow for meaningful comparisons, we also consider the existing state-of-the-art forecasting models. Even more, the forecasting literature has shown that single model predictive accuracy is time-dependent and thus there might not be a single model that outperforms all others at all times. Hence, our paper also compares the forecasts from the MIDAS framework against combined forecasts.

Our findings show that ultra-high frequency data from financial, commodities and macroeconomic assets provide significant predictive gains in monthly oil price forecasts. In particular, the daily realized volatilities from the aforementioned assets reduce the MSPE by almost 68% in 12-months ahead forecasting horizon, relatively to the no-change forecast. Even more, the forecasts based on the daily realized volatilities outperforms the current state-of-the-art models for all horizons, apart from 9-months ahead. We further show that at least in the short-run (up-to 6-month horizon) the use of ultra-high frequency data provides gains in directional accuracy. The results remain robust to several test, including comparison with combined forecasts, forecasting performance during turbulent oil market periods and when using daily asset returns, as opposed to asset volatilities.

The rest of the paper is structured as follows. Section 2 briefly reviews the literature. Section 3 provides a detailed description of the data. Section 4 describes the econometric approach employed in this paper and the forecasting evaluation techniques. Section 5 analyses the findings of the study and Section 6 includes the robustness checks. Section 7 concludes the study.

2. Brief review of the literature

The aim of this section is not to provide an extensive review of the existing literature but rather to highlight the current state-of-the-art and motivate our approach. Table 1 provides a summary of the key econometric models that have been used in the literature, along with their findings.

[TABLE 1 HERE]

One of the early studies in this line of research was conducted by Knetsch (2007), who uses a random walk and futures-based forecasts as benchmarks and investigates whether convenience yield forecasting models exhibit a superior predictive ability. The author considers several definitions for the convenience yield and finds that the convenience yield forecasting models provide superior forecasts for 1 up to 11 months ahead, as well as, superior prediction of the direction of change, compared to the two benchmark models.

Coppola (2008) employs Vector Error Correction Models (VECM) using monthly spot oil prices and a set of futures prices, whereas Murat and Tokat (2009) employ the same methodology for monthly spot oil prices and crack spread futures. Both studies show that the VECM model based on the information extracted from the futures market provide improved forecasts compared to the random walk.

Alquist and Kilian (2010) also focus on the information extracted by the futures market and forecast monthly oil prices using several specifications of futures-based models. For robustness, they compare these forecasts against the random walk, the Hotelling method, as well as, survey-based models. Alquist and Kilian (2010) cannot offer support to the findings of Coppola (2008) and Murat and Tokat (2009), as their findings suggest that the futures-based forecasts are inferior to the random walk forecasts.

Furthermore, Baumeister *et al.* (2013) investigate the usefulness of the product spot and futures spreads of gasoline and heating oil prices against crude oil prices. Using several robustness tests, the authors provide evidence that the futures spreads offer important predictive information of the spot crude oil prices.

Many of the subsequent studies focus on the superior predictive ability of the VAR-based models. For instance, Baumeister and Kilian (2012) show that recursive

VAR-based forecasts[1] based on oil market fundamentals (oil production, oil inventories, global real economic activity) generate lower predictive errors (particularly at short horizons until 6 months ahead) compared to futures-based forecasts, as well as, time-series models (AR and ARMA models), and the no-change forecast. More specifically, the authors use unrestricted VAR, Bayesian VAR (BVAR) and structural VAR (SVAR) with 12 and 24 lags and their findings suggest that the BVAR generate both superior forecasts and higher directional accuracy. Alquist *et al.* (2013) also suggest that VAR-based forecasts have superior predictive ability, at least in the short-run, corroborating the results by Baumeister and Kilian (2012).

Furthermore, Baumeister and Kilian (2014) assess the forecasting ability of a Time-Varying Parameter (TVP) VAR model, as well as, forecast averaging. Their findings show that the TVP-VAR is not able to provide better forecasts compared to the established VAR-based forecasts. Nevertheless, they report that forecast averaging is capable of improving the VAR-based forecasts, although only for the longer horizons.

Another study that also provides support to the findings that the VAR-based models provide superior oil price forecasts is this by Baumeister and Kilian (2016) who use these models to show the main factors that contributed to the decline in oil prices from June 2014 until the end of 2014.

Baumeister and Kilian (2015) and Baumeister *et al.* (2014) extend further this line of research by examining the advantages of forecast combinations based on a set of forecasting models, including the no-change and VAR-based forecasts, as well as, forecasts based on futures oil prices, the price of non-oil industrial raw materials (as per Baumeister and Kilian, 2012), the oil inventories and the spread between the crude oil and gasoline prices. Baumeister and Kilian (2015) also consider a time-varying regression model using price spreads between crude oil and gasoline prices, as well as, between crude oil and heating oil prices. Their results show that equally weighted combinations generate superior predictions and direction of change for all horizons form 1 to 18 months. These findings remain robust to quarterly forecasts for up to 6 quarters ahead. Baumeister *et al.* (2014) further report that higher predictive

[1] The authors use unrestricted VAR, Bayesian VAR and structural VAR (developed by Kilian and Murphy, 2010) with 12 and 24 lags.

accuracy is obtained when forecast combinations are allowed to vary across the different forecast horizons.

Manescu and Van Robays (2014) further assess the effectiveness of forecast combinations, although focusing on the Brent crude oil prices, rather than WTI. More specifically, the authors employ the established oil forecasting frameworks (i.e variants of VAR, BVAR, future-based and random walk), as well as, a DSGE framework. The authors provide evidence similar to Baumeister *et al.* (2014), showing that none of the competing models is able to outperform all others at all times and only the forecast combinations are able to constantly generate the most accurate forecasts for up to 11 months ahead.

More recently, Naser (2016) employs a number of competing models (such as Autoregressive (AR), VAR, TVP-VAR and FAVAR) models) to forecast the monthly WTI crude oil prices, using data from several macroeconomic, financial and geographical variables (such as, CPI, oil futures prices, gold prices, OPEC and non-OPEC oil supply, among others) and compares their predictive accuracy against the Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS) approaches. Naser (2016) finds that the latter approaches exhibit a significantly higher predictive accuracy.

A slightly different approach is adopted by Yin and Yang (2016), who assess the ability of technical indicators to successfully forecast the monthly WTI prices. In particular, they use three well-established technical strategies, namely, the moving average (MA), the momentum (MOM) and on-balance volume averages (VOL), which are then compared against a series of bivariate predictive regressions. For the latter regressions the authors use eighteen different macro-financial indicators (such as, CPI, term spread, dividend yield of the S&P500 index, industrial production, etc.). Their findings suggest that technical strategies are shown to have superior predictive ability compared to the well-established macro-financial indicators.

Thus far, we have documented that the models which seem to exhibit the highest predictive accuracy both in terms of minimising the forecasting error, as well as, of generating the highest directional accuracy are the VAR-based models. Even more, there is evidence that forecast combinations can increase further the forecasting accuracy of the VAR-based models, given that the literature has shown that no single model can outperform all others over a long time period.

Nevertheless, all aforementioned studies primarily use monthly data not only for the crude oil prices and the oil market fundamentals but also for all other macro-financial variables. Baumeister *et al.* (2015) is the only study to use higher frequency financial data (weekly[2]) to forecast the monthly crude oil prices. To do so, they authors employ a Mixed-Data Sampling (MIDAS) framework and compare its forecasting performance against the well-established benchmarks of the no-change and VAR-based forecasts. Interestingly enough, the authors claim that even though the MIDAS framework works well, it does not always perform better than the other competing models and there are cases where it produces forecasts which are inferior to the no-change model. Thus, they maintain that "…not much is lost by ignoring high- frequency financial data in forecasting the monthly real price of oil." (p. 239).

Contrary to Baumeister *et al.* (2015) we maintain that the usefulness of high-frequency financial data in the forecast of oil prices is by no means conclusive. We make such claim given the compelling evidence that financial markets and the oil market have shown to exhibit increased comovements over the last decade, as also aforementioned in Section 1. Furthermore, there is scope to examine further the benefits of high-frequency financial data in forecasting oil prices, given that Baumeister *et al.* (2015) have not used an exhaustive list of high-frequency financial and commodities data, which we consider in this study.

Even more, the bulk literature has concentrated its attention in the forecast of WTI or the refiner`s acquisition cost of imported crude oil prices, ignoring the importance of the Brent crude oil price forecasts. Thus, in this paper we focus on the latter, which is one of the main global oil benchmark, given that a number of institutions, such as the European Central Bank, the IMF and the Bank of England are primarily interested in Brent oil price forecasts, rather than WTI (Manescu and Van Robays, 2014).

[2] Their high-frequency variables include: (i) the spread between the spot prices of gasoline and crude oil; (ii) the spread between the oil futures price and the spot price of crude oil; (iii) cumulative percentage changes in the Commodity Research Bureau index of the price of industrial raw materials, (iv) the US crude oil inventories, (v) the Baltic Dry Index (BDI), (vi) returns and excess returns on oil company stocks, (vii) cumulative changes in the US nominal interest rates, and (viii) cumulative percentage changes in the US trade-weighted nominal exchange rate. Weekly series are constructed from daily data.

3. Data Description

In this study we use both ultra-high and low frequency data. We employ monthly data for the main oil market fundamentals, as these have been identified by the literature. In particular, we use the global economic activity index and Baltic Dry Index (as proxies of the global business cycle), the global oil production and the global oil stocks (as a proxy of oil inventories). We also use the capacity utilisation rate of the oil and gas industry, as an additional measure of oil demand in relation to economic activity. Kaminska (2009) highlights the link between lower oil prices and the substantial decrease in oil and refinery capacity utilisation during the global financial crisis period. The Baltic Dry index, the global oil production and global oil stocks are converted into their log-returns.

The ultra-high frequency data comprise tick-by-tick data of the front-month futures contracts for three major exchange rates (GBP/USD, CAD/USD, EUR/USD), four stock market indices (FTSE100, S&P500, Hang Seng, Euro Stoxx 50), six commodities (Brent crude oil, Gold, Copper, Natural Gas, Palladium, Silver) and the US 10yr T-bills. The tick-by-tick data are used to construct the daily returns and realized volatilities of all aforementioned assets[3]. We also use daily data of the US Economic Policy Uncertainty (EPU) index, which is used, along with the US 10yr T-bills, as proxies of the global macroeconomic volatility[4]. Thus, in total we consider 15 ultra-high frequency time-series, which belong to four different asset classes, namely, *Forex*, *Stocks*, *Commodities* and *Macro*.

The choice of variables is justified by the fact that there is a growing literature that confirms the cross-market transmission effects between the oil, the commodities and the financial markets[5], as well as, the findings related to the financialisation of the

[3] The realized volatility is estimated as the sum of squared intra-day returns and it is adjusted with the close-to-open volatility according to Hansen and Lunde (2005); i.e. minimising the variance of the realized volatility. The intra-day sampling frequency is defined as the highest frequency that minimises the autocovariance bias..

[4] The index is constructed by Baker *et al.* (2016). EPU index is constructed based on three types of underlying components. The first component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty. For more information the reader is directed to http://www.policyuncertainty.com/.

[5] See, *inter alia*, Aloui and Jammazi (2009), Sari *et al.* (2010), Arouri *et al.* (2011), Souček and Todorova (2013, 2014), Mensi *et al.* (2014), Antonakakis *et al.* (2014), Sadorsky (2014), Phan *et al.* (2015), IEA (2015).

oil market, as discussed in Section 1[6]. Furthermore, the aforementioned assets reflect market conditions in Europe, as well as, globally.

The use of asset returns based on the ultra-high frequency data is motivated by the extant literature which documents spillover effects between oil, commodities and financial assets' returns, as discussed in Sections 1 and 2. On the other hand, the use of realized volatilities are predictors of oil prices is related to the arguments put forward by French *et al.* (1986), Engle *et al.* (1987), Bollerslev *et al.* (1988), among others, that expectations related to future asset returns are also influenced by its own current and past variance. Hence, motivated by this argument, we extend it further to assess whether futures oil prices are not only influenced by its own current and past variance, but also by the current and past variances of other assets.

The period of our study spans from August 2003 to August 2015 and it is dictated by the availability of intraday data for the Brent Crude oil futures contracts. Table 2 summarizes the data and the sources from which they have been obtained.

[TABLE 2 HERE]

4. Forecasting models

4.1. MIDAS regression model

We define the log-returns of oil price at a monthly frequency as $y_t = log(OP_t/OP_{t-1})$, and the vector of explanatory variables at a monthly frequency as $\boldsymbol{X}_t = (Gea_t \quad log(Prod_t/Prod_{t-1}) \quad log(Stocks_t/Stocks_{t-1}) \quad Cap_t)'$, where GEA_t, $Prod_t$, $Stocks_t$ and Cap_t denote the, global economic activity, changes in the global oil production, changes in global oil stocks and capacity utilisation rate, respectively. The vector of daily returns or realized volatilities is denoted as $\boldsymbol{X}^{(D)}_{(t)/s}$, where $s = 22$ is the number of daily observations at each month. The MIDAS model with polynomial distributed lag weighting, first proposed by Almon (1965), is expressed as:

$$y_t = \boldsymbol{X}'_{t-i}\boldsymbol{\beta} + \sum\nolimits_{\tau=0}^{k-1} \boldsymbol{X}'^{(D)}_{(t-\tau-is)/s} \left(\sum\nolimits_{j=0}^{p} \tau^j \boldsymbol{\theta}_j\right) + \varepsilon_t, \qquad (1)$$

[6] For a justification of the specific asset prices, which are included in our sample, please refer to Degiannakis and Filis (2016). However, we should also add that the use of exchange rates is also justified by the claim that when forecasting oil prices for countries other than the United States, the inclusion of the exchange rates in the forecasting models is necessary (Baumeister and Kilian, 2014). Finally, the specific series are among the most tradable futures contracts globally.

where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, and $\boldsymbol{\beta}$, $\boldsymbol{\theta}_j$ are vectors of coefficients to be estimated. The p is the dimension of the lag polynomial in the vector parameters $\boldsymbol{\theta}_j$. The k is the number of lagged days to use, which can be less than or greater than s.

The proposed MIDAS model relates the current's month oil price with the low-frequency explanatory variables i months before and the ultra-high frequency explanatory variables $s+\tau$ trading days before. Hence, such a model is able to provide i months-ahead oil price forecasts. For example, if we intend to predict the one-month ahead oil price then the MIDAS model is estimated for $i \geq 1$, thus $is \geq 22$. In the case we intend to predict the three-month ahead oil price then the MIDAS model is estimated for $i \geq 3$, thus $is \geq 66$.

The number of lagged days k is defined for the minimum sum of squared residuals. Thus, at each model estimation the optimum k varies. In order to investigate the adequate number of polynomial order, we run a series of model estimations for various values of p. We conclude that the appropriate dimension of the lag polynomial is $p = 3$.

Denoting the constructed variable based on the lag polynomial as $\widetilde{\boldsymbol{X}}_{j,t} = \sum_{\tau=0}^{k-1} \tau^j \boldsymbol{X}'^{(D)}_{(t-\tau-is)/s}$, the MIDAS model is written as:

$$y_t = \boldsymbol{X}'_{t-i}\boldsymbol{\beta} + \sum\nolimits_{j=0}^{p} \widetilde{\boldsymbol{X}}_{j,t}\boldsymbol{\theta}_j + \varepsilon_t, \tag{2}$$

Thus, the number of vector coefficients to be estimated $\boldsymbol{\theta}_j$ depends on p and not on the number of daily lags k.

Technical information for MIDAS model is available in Andreou *et al.* (2010, 2013). Ghysels *et al.* (2006, 2007) proposed the weighting scheme to be given by the exponential Almon lag polynomial or the Beta weighting. Foroni *et al.* (2015) proposed the unrestricted MIDAS polynomial. Those polynomial specifications work adequately for small values of s.

In total we estimate 29 MIDAS models, using one asset's volatility or return at a time[7]. We denoted MIDAS-RV and MIDAS-RET the MIDAS model based on realized volatilities and returns, respectively. MIDAS forecasts are compared with the models that have been suggested by the literature. In particular, we use a random-walk model (as the no-change forecast), AR(1), AR(12), AR(24) and ARMA(1,1)

[7] Even though we have 15 assets, EPU is considered as a proxy of macroeconomic volatility and thus it is only included in the set of asset volatilities.

models, as well as, VAR-based models. For the latter we use unrestricted VAR models and BVAR models, with three and four endogenous variables. The trivariate VAR models include the changes in the global oil production, the global economic activity index and the Brent crude oil prices, whereas for the four variable VAR models we add the changes in global oil stocks. We should emphasize here that we estimate the VAR models using the level oil prices with 12 and 24 lags. The choice of the aforementioned models is motivated by Baumeister *et al.* (2015), Kilian and Murphy (2014), Baumeister and Kilian (2012), among others.

4.2. Forecast prediction and evaluation

Our forecasts are estimated recursively using an initial sample period of 100 months. The MIDAS predictions are estimated as in eq. 3:

$$OP_{t+h|t} = OP_t \times exp\left(\boldsymbol{X'}_{t-i+h}\boldsymbol{\beta}^{(t)} + \sum_{\tau=0}^{k-1} \boldsymbol{X}'^{(D)}_{\frac{(t-\tau-hs)}{s}} \left(\sum_{j=0}^{p} \tau^j \boldsymbol{\theta}_j^{(t)}\right) + {}^1\!/_2\, \hat{\sigma}_\varepsilon^2\right) \quad (3)$$

For a description of the remaining models' predictions, please refer to Baumeister *et al.* (2015), Kilian and Murphy (2014) and Baumeister and Kilian (2012).

Initially, the monthly forecasting ability of our models is gauged using both the Mean Squared Predicted Error (MSPE) and the Mean Absolute Percentage Predicted Error (MAPPE), relative to the same loss functions of the monthly no-change forecast. All evaluations are taking place based on the level oil prices. A ratio above one would suggest that a forecasting model is not able to perform better than the no-change forecast, whereas the reverse holds true for ratios below 1.

To establish further the forecasting performance of the competing models, we employ the Model Confidence Set (MCS) (Hansen *et al.*, 2011), which identifies the set of the best models which have equal predictive accuracy, according to a loss function. The benefit of the MCS test, relative to other approaches (such as the Diebold Mariano test) is that there is no need for an *a priori* choice of a benchmark model. The MCS test is estimated using two aforementioned loss functions.

For M^0 denoting the initial set of forecasting models, let $\Psi_{n,t}$ be the evaluation function of any model n at month t. We denote the evaluation differential as $d_{n,n^*,t} =$

$\Psi_{n,t} - \Psi_{n^*,t}$, for $n, n^* \in M^0$. The $\Psi_{n,t}$ is the evaluation function under consideration; e.g. for the MSPE, we have $\Psi_{n,t} \equiv \left(OP_{t+s|t} - OP_{t+s}\right)^2$, where $OP_{t+s|t}$ is the s-months-ahead oil price forecast. The null hypothesis $H_{0,M}: E\left(d_{n,n^*,t}\right) = 0$, for $\vee$ $n, n^* \in M$, $M \subset M^0$ is tested against the $H_{1,M}: E\left(d_{n,n^*,t}\right) \neq 0$, for some $n, n^* \in M$.

Finally, we also assess the directional accuracy of our models, using the success ratio, which depicts the number of times a forecasting model is able to predict correctly whether the oil price will increase or decrease. A ratio below 0.5 denotes no directional accuracy, whereas any values above 0.5 suggest an improvement relatively to the no-change forecast. We use the Pesaran and Timmermann (2009) test to assess the significance of the directional accuracy improvements of any model relative to the no-change forecast.

5. Empirical results

5.1. MIDAS-RV models

We start our analysis with the MIDAS-RV and the results are reported in Table 3.

[TABLE 3 HERE]

It is evident from Table 3 that almost all MIDAS-RV models exhibit important gains in forecasting accuracy relatively to the no-change forecast, suggesting that the financial assets' volatilities have significant predictive information for the monthly oil prices. Even more, these gains seem to become quite substantial as the forecasting horizon increases, although this does not hold for all assets. The fact that the forecasting gains, relatively to the no-change forecast, increase as the forecasting horizons extends further out is also observed in Baumeister *et al.* (2015). More specifically, we report gains up to about 68% with our MIDAS-RV model, based on the MPSE in the 12-months-ahead horizon, whereas in the short-run horizons of 1- and 3-months ahead, the predictive gains are 15% and 30%, respectively.

Comparing the MIDAS-RV models performance against all other benchmarks we are able to deduct the conclusion that the former are clearly outperforming. The only exception is the 9-months ahead forecasting horizon where the trivariate BVAR model with 12 lags (3-BVAR(12)) outperforms all others, with predictive gains relatively to the no-change forecast of 38%. We should not lose sight of the fact though, that even in the 9-month horizon, there are still MIDAS-RV models that generate substantial predictive gains which reach the levels of 20%.

Nevertheless, we observe that at least in the short- and medium-rum (up to 6-month horizon), the benchmark models do not seem to provide any gains in forecasting accuracy relatively to the no-change forecasts, as opposed to the models that incorporate the ultra-high frequency volatilities.

It is also important to highlight the fact that as we move further to the forecasting horizon it is a different asset class that provides the highest forecast accuracy. More specifically, in the short-run (1-month ahead) the stock market volatility, and in particular the Eurostoxx 50 volatility, provides the highest predictive gains. In the medium-run (3- and 6-months ahead) the information obtained from the foreign exchange market (GBP/USD volatility) enhances the forecasting accuracy of oil prices, whereas in the long-run we observe that the commodities are assuming the role of the best performing model (PA volatility). This is a very important finding, which has not been previous reported in the literature, and suggests that different assets provide different predictive information for oil prices at the different forecasting horizons.

Given that Brent crude oil is the benchmark used in the European market, the fact that the assets which provide the most valuable predictive information are the Eurostoxx 50 and the GBP/USD volatilities, suggest it is the European rather than the global financial conditions that incorporate important information for the future path of oil prices. Even more, we would anticipate that stock market and foreign exchange volatility would transmit predictive information for oil prices in the short- and medium-run respectively, given that these markets are more short-run oriented. By contrast, the commodities market exhibits a more long-run character, hence the finding that this market provides the most accurate forecasts in the longer-run.

Next, we need to establish whether the gains in the forecasting accuracy that were achieved using the MIDAS-RV models are statistically significantly higher compared to all other models. To do so, we perform the MCS test, which assesses the models that can be included among the set of the best performing models with equal predictive accuracy. The models that can be included in the set of the best performing models are shown in Tables 3 with an asterisk.

The MCS test clearly shows that the best performing models in all forecasting horizons (apart from the 9-month ahead) are the MIDAS-RV models and particularly the MIDAS-RV-XX, MIDAS-RV-BP and MIDAS-RV-PA. This finding is rather important as it reinforces our argument that ultra-high frequency data are capable of providing superior predictive accuracy not only relatively to the no-change forecast, but also to the current state-of-the-art models.

Furthermore, we report the success rations of the competing models (see Table 4). Our findings suggest that the MIDAS-RV models exhibit high directional accuracy, which are particularly evident in the shorter horizons (until 6-months horizon). The directional accuracy ranges between 56% and 67%, depending on the horizon and MIDAS-RV model. Interestingly enough, none of the models is able to achieve significant directional accuracy in the 12-months ahead forecasts.

[TABLE 4 HERE]

5.2. MIDAS-RET models

We proceed further with the examination of whether we can achieve even higher predictive accuracy using asset returns, as opposed to asset volatilities, based on the ultra-high frequency data. The results are shown in Table 5.

[TABLE 5 HERE]

Overall, the results suggest that most MIDAS-RET models are not constantly able to outperform the no-change forecast, as in most cases the ratios of the loss functions are above 1. Even more, in the cases where MIDAS-RET models provide predictive gains, these are not very material. Furthermore, the MIDAS-RET models do not seem to provide any incremental predictive gains compared to the MIDAS-RV models, suggesting that the main predictive information is transmitted to oil prices via the uncertainty that exists in the financial, commodities and macroeconomic assets. The only exception is the MIDAS-RET-CD, which provides important predictive gains in two horizons (3- and 12-months ahead), classifying it among the set of the best performing models (based on the MCS test).

Turning our attention to the directional accuracy of the MIDAS-RET models, we show that even though they improve the directional accuracy of the no-change forecast, they are able to do so only in the short- to medium-run (i.e. up to the 6-month horizon), as reported in Table 6. Nevertheless, this improvement is not higher compared to the MIDAS-RV models, providing further evidence of the superior performance of the latter models compared to MIDAS-RET.

[TABLE 6 HERE]

6. Robustness

6.1 Predictive accuracy during the oil price collapse of 2014-2015

So far we have shown quite convincingly that MIDAS-RV models can provide significant gains on both the forecasting and directional accuracy, not only compared to the no-change forecast but also compared to the current state-of-the-art, as well as the MIDAS-RET models. This is a rather important finding, which highlights the importance of the information that can be extracted from the ultra-high frequency financial and commodities data in forecasting monthly oil prices.

Nevertheless, our out-of-sample forecasting period include the period that Brent crude oil sharply lost more than 50% of its price during the period 2014-2015. Baumeister and Kilian (2016) provide a very good overview of the main consequences of this oil price collapse and the factors that might have contributed to this fall. Oil market stakeholders are primarily interested in successful oil price predictions during oil market volatile periods, given that these are the periods that call for actions to mitigate the adverse effects of sharp oil price changes.

Thus, motivated by this extreme movement in oil prices between June 2014 and August 2015, our next step is to assess the forecasting accuracy of our MIDAS-RV and MIDAS-RET models, relatively to the benchmark models, during this oil collapse period. The results are shown in Table 7.

[TABLE 7 HERE]

The results from Table 7 are rather interesting, as they clearly show the several MIDAS-RV and MIDAS-RET models generate forecasts with the highest predictive accuracy, relative to the no-change forecast. Importantly, we should highlight the fact that during this turbulent period MIDAS-RV models can achieve forecasting gains at the 6-month horizon, which exceed the 60% level (based on the MSPE). Furthermore, MIDAS-RV models can also provide significant predictive gains even for the longer run forecasting horizons (9- and 12-months ahead) that exceed the level of 73% (see MSPE of the MIDAS-PA in the 12-months ahead), although these gains a relatively lower compared to the predictive gains of the trivariate and four-variable BVAR(24) models that exceed the level of 81% in the 12-months ahead. The MIDAS-RET models perform better compared to the full out-of-sample period, nevertheless, they do not outperform the MIDAS-RV models.

In terms of the models that belong to the set with the best performing models (based on the MCS test), these are clearly the MIDAS-RV models until the 6-month horizon, although the MIDAS-RET models with the commodities are also included in the best performing models at the 1-month horizon.

Thus, overall, we maintain that MIDAS models using ultra-high frequency data are useful alternatives (especially for the short- to medium-run forecasting horizons) to the standard models that are currently employed in the literature, although this primarily holds for the use of realized volatilities rather than returns.

Turning to the success ratios (see Table 8), we observe that MIDAS-RV models are among the models with the most significant gains in directional, which exceed the level of 70% and 60%, in short-run and medium-run forecasting horizons. Nevertheless, the tri-variate and four-variable BVAR(24) models exhibit the highest directional accuracy in the 12-month ahead forecasting horizon. The MIDAS-RET provide some improvement on the directional accuracy relatively to the no-change forecast only at the 1-month horizon.

[TABLE 8 HERE]

Overall, the evidence shows that the MIDAS-RV models are not only able to generate superior forecasts but they also exhibit an equal performance in terms of directional accuracy, even during turbulent times.

6.2 MIDAS models based on asset classes' returns and volatilities.

Next, we investigate whether we can increase further the forecasting accuracy of oil prices using the information of the assets' volatilities or returns that belong within a single asset class, as well as, the combined information of all assets' volatilities (returns).

In order to avoid imposing selection and look-ahead biases we employ the Principal Component Analysis (PCA) that captures the combined asset class volatility (return); see for more information Degiannakis and Filis (2017) and Giannone *et al.* (2008). For g denoting the number of asset volatilities (returns) within an asset class, the PCA volatility (returns) components are computed as:

$$\boldsymbol{X}_{(t)/s}^{(D)} = \boldsymbol{\Lambda}^{(g)} \boldsymbol{X}_{(t)/s}^{(PCA)} + \boldsymbol{e}_t^{(g)}, \tag{4}$$

where $\boldsymbol{\Lambda}^{(g)}$ is the matrix of factor loadings, $\boldsymbol{X}_{(t)/s}^{(PCA)}$ is the vector with the common factors, and $\boldsymbol{e}_t^{(g)}$ is the vector of the idiosyncratic component. E.g. for the *Stocks* asset class, we use the volatilities of the g=4 stock market indices to estimate the PCA volatility (return) components; $\boldsymbol{X}_{(t)/s}^{(PCA)} \equiv \begin{bmatrix} RV_{(PCA),X_{(1)},t} \\ \vdots \\ RV_{(PCA),X_{(g)},t} \end{bmatrix}$, where $X_{(g)}$ denotes the daily common factors that are incorporated in the MIDAS-RV-Stocks (or MIDAS-RET-Stocks) models[8]. We apply the same procedure for the remaining three asset classes. Finally, based on PCA we extract the common factors of all assets' returns or volatilities together, which allow us to assess their combined predictive information in models we denote as MIDAS-RV-Combined and MIDAS-RET-Combined. The results are presented in Tables 9 and 10 for the full out-of-sample period and the oil collapse period, respectively.

[TABLE 9 HERE]

[TABLE 10 HERE]

Tables 9 and 10 reveal that even though some of the combined asset classes' volatilities (e.g. the MIDAS-RV-Forex and MIDAS-RV-Stocks) provide predictive gains relatively to the no-change forecast in almost forecast horizons, they cannot outperform the forecasting accuracy of the MIDAS-RV models with single asset volatility, as shown in Tables 3 and 7. This also hold true for the MIDAS-RET models. These results also apply for the MIDAS-RV-Combined and MIDAS-RET-Combined, suggesting that we cannot improve further the forecasting accuracy of oil prices by combining all assets' volatilities or returns together.

Similar conclusions can be drawn for the directional accuracy of the MIDAS models based on the four asset classes (see Table 11).

[TABLE 11 HERE]

6.3 Forecast combinations

Finally, we examine whether forecast combinations are able to outperform the MIDAS-RV models, which are the best performing models thus far. To do so, we construct three simple average models, namely, the simple average of all benchmark models, the simple average of all MIDAS-RV and MIDAS-RET models and the

---

[8] For the returns of the stock market indices, we estimate the PCA return components, $\boldsymbol{X}_{(t)/s}^{(PCA)} \equiv \begin{bmatrix} x_{(PCA),X_{(1)},t} \\ \vdots \\ x_{(PCA),X_{(g)},t} \end{bmatrix}$.

simple average of all competing models[9]. The results are reported in Table 12, whereas Table 13 exhibits the directional accuracy of the forecast combinations.

[TABLE 12 HERE]

[TABLE 13 HERE]

It is evident from Table 12 that forecast combinations, either in the full out-of-sample period or the oil collapse period, are able to perform better than the no-change forecast, nevertheless they cannot provide incremental gains relatively to the best MIDAS-RV models that were identified in Tables 3 and 7. The only exception is the forecast combination based on all benchmark models in the 9-month ahead forecasting horizon, which improves the predictive gains of the trivariate BVAR(12). In terms of directional accuracy, we are able to show that forecast combinations do not demonstrate improved directional accuracy compared to the MIDAS-RV models.

Overall, the robustness tests confirm our evidence that asset volatilities which are constructed using ultra-high frequency data provide significant superior predictive accuracy, as well as, directional accuracy for the monthly oil prices.

7. Conclusion

The aim of this study is to forecast the monthly oil prices using information for ultra-high frequency data of financial, commodities and macroeconomic assets. We do so using a MIDAS model and by constructing daily returns and realized volatilities from the ultra-high frequency data. Our data span from August 2003 until August 2015. The out-of-sample period runs from December 2011 until August 2015.

We compare the forecasts generated by our MIDAS-RV and MIDAS-RET models against the no-change forecast, as well as, the current state-of-the-art forecasting models. The findings of the study show that MIDAS-RV models exhibit significantly higher predictive ability and directional accuracy relatively to the no-change forecast, as well as, to the other benchmark models. Furthermore, we report that the predictive gains relatively to the no-change forecast exceed the level of 68% at the 12-month ahead forecasting horizon. These results hold true even when we only consider the predictive accuracy of our models during the oil price collapse period of 2014-2015.

[9] The construction of other forecast combinations suggested in the literature, i.e. the ordinary least-squares estimate for the forecasts combination weights, the performance-based weights or the trimming approach which discards the worst performing model, usually suffer from forward looking bias, as the weights are estimated based on the out-of-sample forecasting performance of the competing models.

The results also suggest that the MIDAS-RET models can also provide predictive gains relatively to the no-change forecast and the other benchmark models (mainly for the oil collapse period), although their performance is not superior to the MIDAS-RV models.

For robustness purposes we estimate MIDAS models based on asset classes' volatilities and returns and the findings confirm that the aggregated information from the asset classes cannot provide incremental superior predictive accuracy relatively to the MIDAS-RV models. These results remain robust even when forecast combinations are employed.

Hence, we maintain that the use of ultra-high frequency data is able to enhance the predictive accuracy of the monthly oil price forecasts. Nevertheless, this study does not report a single asset volatility that constantly provides the most accurate forecasts. Thus, we maintain that even though ultra-high frequency data are valuable for monthly oil price forecast, there is still scope to extend further this line of research. For instance, future research could further test the usefulness of ultra-high frequency data in forecasting oil prices using financial instruments that approximate aggregated asset classes, such as the US equity index futures, USD index futures and the S&P-GSCI futures.

Acknowledgements

The authors acknowledge the support of the European Union's Horizon 2020 research and innovation programme, which has funded them under the Marie Sklodowska-Curie grant agreement No 658494.

References

Akram, Q. F. (2009). Commodity prices, interest rates and the dollar. *Energy Economics*, 31(6), 838-851.

Aloui, C., & Jammazi, R. (2009). The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach. *Energy Economics*, *31*(5), 789-799.

Alquist, R., & Kilian, L. (2010). What do we learn from the price of crude oil futures?. *Journal of Applied Econometrics*, *25*(4), 539-573.

Alquist, R., Kilian, L., & Vigfusson, R. J. (2013). Forecasting the price of oil. *Handbook of economic forecasting*, *2*, 427-507.

Almon, S. (1965). The distributed lag between capital appropriations and expenditures. *Econometrica: Journal of the Econometric Society*, 178-196.

Andreou, E., Ghysels, E., & Kourtellos, A. (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics*, *158*(2), 246-261.

Andreou, E., Ghysels, E., & Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how?. *Journal of Business & Economic Statistics*, *31*(2), 240-251.

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics*, *44*, 433-447.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. *Journal of International Money and Finance*, *30*(7), 1387-1405.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636.

Barnato, K. (2016). Here's the key challenge Draghi will face at this week's ECB meeting, CNBC, 30th May, http://www.cnbc.com/2016/05/30/heres-the-key-challenge-draghi-will-face-at-this-weeks-ecb-meeting.html

Barsky, R. B., & Kilian, L. (2004). Oil and the Macroeconomy since the 1970s. *The Journal of Economic Perspectives*, *18*(4), 115-134.

Baumeister, C., & Kilian, L. (2012). Real-time forecasts of the real price of oil. *Journal of Business & Economic Statistics*, 30(2), 326-336.

Baumeister, C., Kilian, L., & Zhou, X. (2013). Are product spreads useful for forecasting? An empirical evaluation of the Verleger hypothesis (No. 2013-25). Bank of Canada Working Paper.

Baumeister, C., & Kilian, L. (2014). What central bankers need to know about forecasting oil prices. *International Economic Review*, *55*(3), 869-889.

Baumeister, C., & Kilian, L. (2015). Forecasting the real price of oil in a changing world: a forecast combination approach. *Journal of Business & Economic Statistics*, *33*(3), 338-351.

Baumeister, C., & Kilian, L. (2016). Understanding the Decline in the Price of Oil since June 2014. *Journal of the Association of Environmental and Resource Economists*, *3*(1), 131-158.

Baumeister, C., Kilian, L., & Lee, T. K. (2014). Are there gains from pooling real-time oil price forecasts?. *Energy Economics*, *46*, S33-S43.

Baumeister, C., Guérin, P., & Kilian, L. (2015). Do high-frequency financial data help forecast oil prices? The MIDAS touch at work. *International Journal of Forecasting*, *31*(2), 238-252.

Baumeister, C., & Peersman, G. (2013). Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics*, *5*(4), 1-28.

Blas, J., & Kennedy, S. (2016). For Once, Low Oil Prices May Be a Problem for World's Economy, Bloomberg, 2nd February, https://www.bloomberg.com/news/articles/2016-02-02/for-once-low-oil-prices-may-be-a-problem-for-world-s-economy.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of political Economy*, 96(1), 116-131.

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. *Journal of International Money and Finance*, *42*, 38-70.

Clements, M. P., & Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States. *Journal of Business & Economic Statistics*, *26*(4), 546-554.

Clements, M. P., & Galvão, A. B. (2009). Forecasting US output growth using leading indicators: An appraisal using MIDAS models. *Journal of Applied Econometrics*, *24*(7), 1187-1206.

Coppola, A. (2008). Forecasting oil price movements: Exploiting the information in the futures market. *Journal of Futures Markets*, 28(1), 34-56.

Degiannakis, S. & Filis, G. (2017). Forecasting oil price realized volatility: A new approach, https://mpra.ub.uni-muenchen.de/69105/1/MPRA_paper_69105.pdf

ECB (2016). Economic Bulletin, Issue 4, European Central Bank. https://www.ecb.europa.eu/pub/pdf/other/eb201604_focus01.en.pdf?48284774d83e30563e8f5c9a50cd0ea2.

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, *42*(6), 1137-1159.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: the ARCH-M model. *Econometrica: Journal of the Econometric Society*, 391-407.

Fattouh, B., Kilian, L., & Mahadeva, L. (2013). The Role of Speculation in Oil Markets: What Have We Learned So Far?. *The Energy Journal*, *34*(3), 7.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1), 3-29.

Foroni, C., Marcellino, M., & Schumacher, C. (2015). Unrestricted mixed data sampling (MIDAS): MIDAS regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *178*(1), 57-82.

Giannone, D., L. Reichlin and D. Small (2008). Nowcasting: The real- time informational content of macroeconomic data. Journal of Monetary Economics, 55(4), 665–676.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, *131*(1), 59-95.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews*, *26*(1), 53-90.

Ghysels, E., & Wright, J. H. (2009). Forecasting professional forecasters. *Journal of Business & Economic Statistics*, *27*(4), 504-516.

Hamilton, J. D. (2008). Daily Monetary Policy Shocks and the Delayed Response of New Home Sales, *Journal of Monetary Economics*, 55, 1171-1190.

Hamilton, J. D. (2009a). Causes and Consequences of the Oil Shock of 2007–08. *Brookings Papers on Economic Activity*.

Hamilton, J. D. (2009). Understanding Crude Oil Prices. *The Energy Journal,* 30(2), 179-206.

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a GARCH (1, 1)? *Journal of Applied Econometrics*, *20*(7), 873-889.

Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica*, 79(2), 453-497.

IEA (2015). What drives crude oil prices? US International Energy Administration, July 07. https://www.eia.gov/finance/markets/spot_prices.cfm

IMF (2016). World Economic Outlook – Too slow for too long, International Monetary Fund: Washington DC. https://www.imf.org/external/pubs/ft/weo/2016/01/pdf/text.pdf.

Kaminska, I. (2009). Just how big a problem is falling capacity utilisation?, Financial Times, 27th April, https://ftalphaville.ft.com/2009/04/27/55161/just-how-big-a-problem-is-falling-capacity-utilisation/

Kilian, L. (2009). Not All Oil Price Shocks are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market? *American Economic Review*, 99 (3), 1053-1069.

Kilian, L., & Hicks, B. (2013). Did unexpectedly strong economic growth cause the oil price shock of 2003–2008?. *Journal of Forecasting*, *32*(5), 385-394.

Kilian, L., & Lee, T. K. (2014). Quantifying the speculative component in the real price of oil: The role of global oil inventories. *Journal of International Money and Finance*, *42*, 71-87.

Kilian, L., & Murphy, D. (2010). Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market VAR Models. http://www-personal.umich.edu/~lkilian/km042810.pdf.

Kilian, L., & Murphy, D. (2012). Why agnostic sign restrictions are not enough: understanding the dynamics of oil market VAR models. *Journal of the European Economic Association*, *10*(5), 1166-1188.

Kilian, L., & Murphy, D. (2014). The Role of Inventories and Speculative Trading in the Global Market for Crude Oil, *Journal of Applied Econometrics*, 29, 454–78.

Knetsch, T. A. (2007). Forecasting the price of crude oil via convenience yield predictions. *Journal of Forecasting*, *26*(7), 527-549.

Lippi, F., & Nobili, A. (2012). Oil and the macroeconomy: a quantitative structural analysis. *Journal of the European Economic Association*, *10*(5), 1059-1083.

Manescu, C., & Van Robays, I. (2014). *Forecasting the Brent oil price: addressing time-variation in forecast performance* (No. 1735). European Central Bank.

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S. M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics*, *43*, 225-243.

Murat, A., & Tokat, E. (2009). Forecasting oil price movements with crack spread futures. *Energy Economics*, *31*(1), 85-90.

Naser, H. (2016). Estimating and forecasting the real prices of crude oil: A data rich model using a dynamic model averaging (DMA) approach. *Energy Economics*, 56, 75-87.

Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2015). Oil price and stock returns of consumers and producers of crude oil. *Journal of International Financial Markets, Institutions and Money*, *34*, 245-262.

Sadorsky, P. (2014). Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. *Energy Economics*, *43*, 72-81.

Sari, R., Hammoudeh, S., & Soytas, U. (2010). Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, *32*(2), 351-362.

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, *24*, 42-65.

Souček, M., & Todorova, N. (2013). Realized volatility transmission between crude oil and equity futures markets: A multivariate HAR approach. *Energy Economics*, *40*, 586-597.

Souček, M., & Todorova, N. (2014). Realized volatility transmission: The role of jumps and leverage effects. *Economics Letters*, *122*(2), 111-115.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, *68*(5), 54-74.

Yin, L., & Yang, Q. (2016). Predicting the oil prices: Do technical indicators help?. *Energy Economics*, 56, 338-350.

TABLES

Table 1: Summary of the empirical findings

Authors	Forecasting frequency	Forecasting models	Forecasting horizon	Best performing model(s)
Knetsch (2007)	Monthly forecasts	RBF with CY, NCF, FBF, CF	1-11 months ahead	CY-based forecasts
Coppola (2008)	Monthly forecasts	NCF, VECM, FBF	1 month ahead	VECM
Murat and Tokat (2009)	Weekly forecasts	NCF, VECM	1 month ahead	VECM
Alquist and Kilian (2010)	Monthly forecasts	NCF, FBF, HF, SBF	1-12 months ahead	NCF
Baumeister and Kilian (2012)	Monthly forecasts	NCF, VAR, BVAR, FBF, AR, ARMA	1-12 months ahead	BVAR
Alquist et al (2013)	Monthly forecasts	NCF, AR, ARMA, VAR, FBF	1-12 months ahead	VAR but also AR and ARMA (in short run), NCF (in long run)
Baumeister and Kilian (2014)	Quarterly forecasts	NCF, FBF, VAR, BVAR, TVP, RBF, CF	4 quarters ahead	VAR in the short run
Baumeister *et al*. (2014)	Monthly and Quarterly forecasts	NCF, VAR, FBF, RBF, CF	1-24 months ahead, 1-8 quarters ahead	CF
Manescu and Van Robays (2014)	Monthly forecasts	NCF, FBF, RBM, VAR, BVAR, DSGE, RW, CF	1-11 quarters	CF
Baumeister and Kilian (2015)	Monthly and Quarterly forecasts	NCF, VAR, FBF, RBF, TV-RBF, CF	1-24 months ahead, 1-8 quarters ahead	CF
Baumeister et al (2015)	Monthly forecasts	NCF, VAR, PSF, RBF, MIDAS, MF-VAR	1-24 months ahead	RBF with oil inventories
Naser (2016)	Monthly forecasts	FAVAR, VAR, RBF with factors, DMA, DMS	1-12 months ahead	DMA and DMS

Yin and Yang (2016)	Monthly forecasts	RBF with technical indicators, VAR, BVAR, TVPVAR, CF	1 month ahead	RBF with technical indicators
Baumeister *et al.* (2017)	Monthly forecasts	NCF, FBF, PSF, CF	1-24 months ahead	PSF

Notes: BVAR=Bayesian VAR models, CF=combined forecasts, CY=Convenience yield, DMA=Dynamic model averaging, DMS=Dynamic model selection, FBF=Futures-based forecasts, HF=Hotelling method, MF-VAR=Mixed-frequency VAR, MIDAS=Mixed Data Sampling, NCF=No-change forecasts, PSF=Product spreads forecasts, RBF=Regression-based forecasts, SBF=Survey-based forecasts, TV-RBF=Time-varying regression-based forecasts, VAR=Vector Autoregressive models.

Table 2: Variable description and data sources.

Name	Acronym	Description/Frequency	Source
Global Economic Activity Index	GEA	Proxy for global business cycle. Monthly data.	Lutz Kilian website (http://www-personal.umich.edu/~lkilian/)
Baltic Dry Index	BDI	Proxy for global business cycle. Monthly data.	Datasteam
Global Oil Production	PROD	Proxy for oil supply. Monthly data.	Energy Information Administation
Global Oil Stocks	STOCKS	Proxy for global oil inventories. Monthly data	Energy Information Administation
Capacity Utilisation Rate	CAP	Proxy for oil demand in relation to economic activity. Monthly data	Federal Reserve Economic Data
Brent Crude Oil	CO	Tick-by-tick data of the front-month futures prices	TickData
GBP/USD exchange rate	BP	Tick-by-tick data of the front-month futures prices	TickData
CAD/USD exchange rate	CD	Tick-by-tick data of the front-month futures prices	TickData
EUR/USD exchange rate	EC	Tick-by-tick data of the front-month futures prices	TickData
FTSE100 index	FT	Tick-by-tick data of the front-month futures prices	TickData
S&P500 index	SP	Tick-by-tick data of the front-month futures prices	TickData
Hang Seng index	HI	Tick-by-tick data of the front-month futures prices	TickData
Euro Stoxx 50 index	XX	Tick-by-tick data of the front-month futures prices	TickData
Gold	GC	Tick-by-tick data of the front-month futures prices	TickData
Copper	HG	Tick-by-tick data of the front-month futures prices	TickData
Natural Gas	NG	Tick-by-tick data of the front-month futures prices	TickData
Palladium	PA	Tick-by-tick data of the front-month futures prices	TickData
Silver	SV	Tick-by-tick data of the front-month futures prices	TickData
US 10yr T-bills	TY	Tick-by-tick data of the front-month futures prices	TickData
Economic Policy Uncertainty Index	EPU	Proxy for the US macroeconomic volatility. Daily data.	Baker *et al.* (2016)

Table 3: Forecasting monthly oil prices - Benchmark and MIDAS-RV models. Evaluation period: 2011.12-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.9730**	1.0297	1.0073	**0.9735**	**0.9777**	**0.9500**	**0.9948**	**0.9771**	**0.9679**	**0.9705**
ARMA(1,1)	**0.9739**	1.0436	1.0143	**0.9685**	**0.9728**	**0.9627**	1.0156	**0.9779**	**0.9611**	**0.9641**
AR(12)	1.0327	1.0455	1.0323	1.0477	1.0545	1.0878	1.0776	1.0467	1.0813	1.0903
AR(24)	1.0013	1.0011	1.0014	1.0008	**0.9992**	1.0066	1.0034	1.0026	1.0006	**0.9972**
3-VAR(12)	1.4614	1.6930	1.4154	**0.8932**	**0.6942**	2.4851	2.8562	2.1953	**0.8567**	**0.4953**
3-VAR(24)	3.6851	2.0039	1.3245	**0.9587**	**0.7714**	11.8383	3.1099	1.4655	**0.9154**	**0.6344**
4-VAR(12)	1.7398	1.9557	1.9424	1.1202	**0.7991**	3.6381	4.5889	5.2078	1.7593	**0.6783**
4-VAR(24)	3.7139	2.0161	1.3283	**0.9626**	**0.7735**	11.9459	3.1386	1.4709	**0.9190**	**0.6369**
3-BVAR(12)	1.1128	1.0249	**0.8877**	**0.8025***	**0.6737**	1.2625	1.1292	**0.7579**	**0.6215***	**0.4520**
3-BVAR(24)	4.1202	2.1044	1.3075	**0.8944**	**0.6733**	14.3190	3.3762	1.3834	**0.7950**	**0.4863**
4-BVAR(12)	1.1160	1.0266	**0.8905**	**0.8038**	**0.6743**	1.2664	1.1279	**0.7599**	**0.6230**	**0.4524**
4-BVAR(24)	4.1203	2.1045	1.3075	**0.8944**	**0.6733**	14.3191	3.3763	1.3834	**0.7950**	**0.4863**
MIDAS-RV-CO	**0.9369**	**0.9998**	**0.8210**	**0.8717**	1.0319	**0.9474**	1.1376	**0.7028**	**0.8341**	1.2504
MIDAS-RV-FT	**0.9312**	1.0453	**0.8696**	1.0328	**0.9697**	**0.9632**	1.1292	**0.7796**	1.1950	1.0275
MIDAS-RV-SP	**0.9303**	**0.9151**	**0.9099**	1.2465	**0.9852**	**0.9718**	**0.8819**	**0.8561**	1.7304	1.0549
MIDAS-RV-XX	**0.8999***	**0.8981**	**0.9343**	1.0126	**0.8146**	**0.8440***	**0.8089**	**0.9102**	1.1815	**0.7569**
MIDAS-RV-HI	**0.9452**	**0.9817**	**0.9618**	1.5920	1.2453	**0.9582**	**0.9612**	1.0639	3.0822	1.7642
MIDAS-RV-BP	**0.9526**	**0.8384***	**0.7554***	**0.8960**	**0.8668**	1.0122	**0.6956***	**0.6280***	**0.8820**	**0.8038**
MIDAS-RV-CD	**0.9032**	**0.8968**	**0.8560**	**0.9710**	1.4640	**0.9351**	**0.8193**	**0.7947**	1.0245	2.2432
MIDAS-RV-EC	**0.9587**	**0.8938**	**0.8162**	**0.9369**	**0.7599**	1.0637	**0.7770**	**0.6730**	**0.9218**	**0.6321**
MIDAS-RV-GC	1.0266	1.1385	1.0410	1.2246	**0.7948**	1.0438	1.2770	1.2712	1.8171	**0.7056**
MIDAS-RV-HG	**0.9598**	**0.9680**	**0.8452**	**0.9426**	**0.8688**	**0.9917**	**0.9665**	**0.7554**	**0.9488**	**0.9026**

MIDAS-RV-NG	**0.9965**	1.0834	**0.9216**	1.0423	**0.9911**	1.0749	1.3582	**0.9609**	1.3522	1.1247
MIDAS-RV-PA	**0.9545**	1.0699	1.1328	**0.8561**	**0.5271***	**0.9677**	1.2014	1.2771	**0.7946**	**0.3233***
MIDAS-RV-SV	**0.9953**	1.1354	1.0397	1.1034	**0.8678**	1.0355	1.3437	1.3126	1.4175	**0.8092**
MIDAS-RV-TY	**0.9425**	**0.9430**	1.1409	1.3810	**0.7070**	**0.9405**	**0.9811**	1.3195	2.3787	**0.5442**
MIDAS-RV-EPU	**0.9475**	1.0344	**0.9240**	1.5993	**0.9640**	**0.9779**	1.1650	**0.8967**	2.8471	1.0115

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 4: Success ratios of benchmarks and MIDAS-RV models. Evaluation period: 2011.12-2015.8

	Success Ratio				
Model:	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.5581**	0.3902	0.4737	0.4286	0.3438
ARMA(1,1)	**0.5814***	0.4146	0.4737	0.4286	0.3125
AR(12)	0.3721	0.4878	0.4474	0.3714	0.3438
AR(24)	0.3953	0.4634	0.4737	0.3714	0.3438
3-VAR(12)	**0.5814**	0.3415	0.5000	**0.5143**	0.4063
3-VAR(24)	0.3953	0.4390	0.4211	0.4571	0.4063
4-VAR(12)	0.4884	0.3171	0.5000	**0.5429***	0.3750
4-VAR(24)	0.3953	0.4390	0.4211	0.4286	0.4063
3-BVAR(12)	0.4884	**0.5366**	**0.5263**	**0.5143**	0.5000
3-BVAR(24)	0.4884	**0.5122**	0.5000	**0.5143**	**0.5313**
4-BVAR(12)	**0.5349**	**0.5366**	**0.5263**	**0.5143**	0.5000
4-BVAR(24)	0.4884	**0.5122**	0.5000	**0.5143**	**0.5313**
MIDAS-RV-CO	**0.5116**	0.4878	**0.6053***	**0.5143**	0.2813
MIDAS-RV-FT	**0.5581**	**0.5366**	**0.5526**	0.4571	0.3125
MIDAS-RV-SP	0.4884	0.4878	0.5000	0.4286	0.3438
MIDAS-RV-XX	**0.5349**	**0.5122**	**0.5263**	**0.5429***	0.2813
MIDAS-RV-HI	**0.5349**	0.4878	0.4474	0.3714	0.3438
MIDAS-RV-BP	**0.6047**	**0.5122**	**0.6579****	**0.5143**	0.3125
MIDAS-RV-CD	**0.6744****	**0.5122**	**0.5526**	0.4571	0.3438
MIDAS-RV-EC	**0.5581**	0.4878	0.5000	0.4857	0.2500
MIDAS-RV-GC	0.4651	0.4634	0.4737	0.4286	0.3125
MIDAS-RV-HG	**0.6047***	**0.5366**	0.4737	0.4857	0.3125
MIDAS-RV-NG	0.4884	0.4390	0.5000	**0.5143**	0.2500
MIDAS-RV-PA	**0.5581**	0.4390	0.4211	**0.5429***	0.4063
MIDAS-RV-SV	0.4884	0.4878	0.5000	0.4571	0.3438
MIDAS-RV-TY	**0.5116**	**0.5366**	0.4737	0.4000	0.2813
MIDAS-RV-EPU	**0.5814**	**0.5610***	0.4474	0.3714	0.3125

Note: The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively. Bold face denotes improvement of the directional accuracy relatively to the no-change forecast.

Table 5: Forecasting monthly oil prices – MIDAS-RET models. Evaluation period: 2011.12-2015.8

	MAPPE					MSPE				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
MIDAS-RET-CO	**0.9281**	1.0909	**0.9970**	1.2859	1.3799	**0.9192**	1.1015	1.0095	1.8187	2.2511
MIDAS-RET-FT	1.0374	1.0437	1.3488	1.4559	1.0807	1.0597	**0.9747**	2.1940	2.3881	1.3293
MIDAS-RET-SP	**0.9603**	**0.9055**	1.0967	1.3611	1.8250	**0.8756**	**0.8934**	1.1954	2.2493	3.4728
MIDAS-RET-XX	1.1158	1.0365	1.1272	2.2701	**0.9355**	1.1097	1.0236	1.9332	6.6529	1.0420
MIDAS-RET-HI	**0.9743**	**0.9101**	1.1955	1.7927	1.0475	**0.9478**	**0.7933**	1.6618	3.9176	1.2709
MIDAS-RET-BP	1.0988	1.2602	1.2588	1.5200	1.0968	1.1592	1.8422	1.9347	2.4557	1.2962
MIDAS-RET-CD	1.1024	**0.7625***	1.0667	1.6392	**0.5380***	1.1323	**0.7111***	1.2580	3.3350	**0.3645***
MIDAS-RET-EC	1.0386	1.1835	1.0672	2.2144	1.4114	1.0623	1.6374	1.3344	5.3958	2.1255
MIDAS-RET-GC	1.0785	1.2083	1.2841	1.5201	1.1308	1.0704	1.4603	1.7321	2.2984	1.3456
MIDAS-RET-HG	1.0729	1.0278	1.4565	1.2768	**0.8927**	1.1475	1.2863	2.7099	1.8640	**0.9867**
MIDAS-RET-NG	1.0942	1.1516	1.4696	1.4382	**0.9755**	1.1578	1.4379	2.3460	2.3790	1.0522
MIDAS-RET-PA	1.0406	1.4164	1.2049	1.1283	1.7149	1.0477	2.2970	1.8342	1.4566	2.9151
MIDAS-RET-SV	1.0758	1.2160	1.2808	1.0123	1.6872	1.2265	1.8575	2.0911	1.1178	3.0539
MIDAS-RET-TY	**0.9723**	1.0370	1.3589	2.6200	1.7797	**0.9580**	**0.9348**	2.0311	8.3700	3.8064

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test, along with the best models from Table 3.

Table 6: Success ratios of MIDAS-RET models. Evaluation period: 2011.12-2015.8

	Success ratio				
Model:	1-month	3-months	6-months	9-months	12-months
MIDAS-RET-CO	**0.5814***	0.3659	0.4474	0.4857	0.2188
MIDAS-RET-FT	**0.5116**	**0.5122**	**0.5789***	0.4571	0.1875
MIDAS-RET-SP	**0.5116**	**0.6098***	0.4737	0.4571	0.2500
MIDAS-RET-XX	**0.5116**	0.4878	**0.5263**	0.4286	0.2813
MIDAS-RET-HI	**0.5349**	**0.5122**	**0.5263**	0.4286	0.2500
MIDAS-RET-BP	0.4884	0.4390	0.4737	0.4571	0.2188
MIDAS-RET-CD	**0.5116**	**0.5366**	0.5000	0.4571	0.2813
MIDAS-RET-EC	0.3953	**0.5366**	**0.5789***	0.4286	0.2500
MIDAS-RET-GC	0.4884	0.4390	0.4474	0.4286	0.2500
MIDAS-RET-HG	0.4651	**0.5610***	0.5000	0.4857	0.3438
MIDAS-RET-NG	**0.5581**	**0.5122**	**0.5789***	**0.5143**	0.2188
MIDAS-RET-PA	**0.5116**	0.4634	0.5000	0.4571	0.2813
MIDAS-RET-SV	0.4884	0.4390	**0.5526**	0.4857	0.2813
MIDAS-RET-TY	0.4884	**0.5610***	0.5000	0.3143	0.3125

Note: The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively. Bold face denotes improvement of the directional accuracy relatively to the no-change forecast.

Table 7: Forecasting monthly oil prices during the oil collapse period – Benchmark, MIDAS-RV and MIDAS-RET models. Evaluation period: 2014.6-2015.8.

	MAPPE					MSPE				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.9684**	1.0071	**0.9826**	**0.9749**	**0.9872**	**0.9500**	**0.9279**	**0.9496**	**0.9589**	**0.9762**
ARMA(1,1)	**0.9569**	1.0079	**0.9827**	**0.9660**	**0.9840**	**0.9369**	**0.9143**	**0.9387**	**0.9451**	**0.9700**
AR(12)	1.0085	1.0055	1.0121	1.0209	1.0290	1.0146	1.0113	1.0200	1.0382	1.0563
AR(24)	**0.9998**	**0.9992**	**0.9998**	**0.9998**	**0.9992**	**0.9999**	1.0003	1.0002	**0.9996**	**0.9983**
3-VAR(12)	1.1564	1.1208	**0.8408**	**0.6800**	**0.6099**	1.5728	1.1959	**0.8409**	**0.5193**	**0.3951**
3-VAR(24)	4.2741	2.2743	1.3756	**0.9432**	**0.8213**	15.1141	3.5331	1.4639	**0.8857**	**0.6876**
4-VAR(12)	1.1779	1.1566	**0.8841**	**0.6841**	**0.6226**	1.6030	1.2727	**0.8487**	**0.5299**	**0.4059**
4-VAR(24)	4.2953	2.2840	1.3737	**0.9426**	**0.8211**	15.2499	3.5552	1.4619	**0.8850**	**0.6879**
3-BVAR(12)	**0.9769**	**0.8379**	**0.7240**	**0.6332**	**0.5355**	**0.9187**	**0.7315**	**0.5679**	**0.4235**	**0.3100**
3-BVAR(24)	2.6136	1.3260	**0.7588**	**0.4984***	**0.4140***	5.7729	1.2227	**0.4583**	**0.2570***	**0.1825***
4-BVAR(12)	**0.9895**	**0.8445**	**0.7283**	**0.6337**	**0.5358**	**0.9283**	**0.7297**	**0.5686**	**0.4239**	**0.3105**
4-BVAR(24)	2.6136	1.3260	**0.7588**	**0.4984**	**0.4140**	5.7731	1.2228	**0.4583**	**0.2570***	**0.1825***
MIDAS-RV-CO	**0.8607***	**0.9241**	**0.7675**	**0.8575**	**0.8012**	**0.8249**	**0.7046**	**0.5818**	**0.7685**	**0.6528**
MIDAS-RV-FT	**0.8629***	**0.9855**	**0.7873**	**0.9455**	**0.9577**	**0.9162**	**0.8571**	**0.6113**	**0.8971**	**0.9166**
MIDAS-RV-SP	**0.8689***	**0.8642**	**0.8260**	1.0564	**0.9086**	**0.8727**	**0.6574**	**0.6655**	1.1240	**0.8299**
MIDAS-RV-XX	**0.8515***	**0.8712**	**0.8220**	**0.9639**	**0.8266**	**0.8136**	**0.7143**	**0.6650**	**0.9496**	**0.6966**
MIDAS-RV-HI	**0.8729**	**0.9626**	**0.8223**	1.0979	1.3997	**0.8474**	**0.8483**	**0.6842**	1.2476	1.9717
MIDAS-RV-BP	**0.9052**	**0.8769**	**0.6884**	**0.8608**	**0.8164**	**0.9419**	**0.6489**	**0.4759**	**0.7810**	**0.6803**
MIDAS-RV-CD	**0.7827***	**0.8387***	**0.7271**	**0.8919**	1.3627	**0.7210***	**0.6104***	**0.5313**	**0.8056**	1.8671
MIDAS-RV-EC	**0.8843**	**0.7946***	**0.6375***	**0.7880**	**0.7071**	**0.9275**	**0.5739***	**0.3916***	**0.6443**	**0.5093**
MIDAS-RV-GC	**0.9343**	1.0477	**0.8275**	**0.9964**	**0.7434**	**0.9012**	**0.9691**	**0.6951**	1.0130	**0.5815**
MIDAS-RV-HG	**0.8881**	**0.9298**	**0.7261**	**0.8990**	**0.7182**	**0.8580**	**0.7548**	**0.5304**	**0.8168**	**0.5371**
MIDAS-RV-NG	**0.8978**	1.0298	**0.7437**	**0.8311**	1.0543	**0.8239**	1.0335	**0.5925**	**0.7432**	1.1184

MIDAS-RV-PA	**0.9063**	**0.9758**	**0.9556**	**0.8519**	**0.4963**	**0.8647**	**0.8456**	**0.8853**	**0.7558**	**0.2635**
MIDAS-RV-SV	**0.9316**	1.0090	**0.8466**	**0.9921**	**0.8839**	**0.9306**	**0.9175**	**0.7087**	1.0337	**0.8017**
MIDAS-RV-TY	**0.8958**	**0.8758**	**0.9062**	1.0258	**0.7545**	**0.8894**	**0.7035**	**0.7866**	1.1111	**0.5796**
MIDAS-RV-EPU	**0.8916**	**0.7906***	**0.8020**	1.3886	**0.9869**	**0.8565**	**0.5861***	**0.6404**	1.8961	**0.9922**
MIDAS-RET-CO	**0.9121**	**0.9850**	**0.8789**	**0.8534**	**0.8656**	1.0201	**0.8639**	**0.7434**	**0.7482**	**0.7611**
MIDAS-RET-FT	**0.9028**	**0.9819**	**0.8307**	**0.9972**	**0.8614**	**0.8959**	**0.8307**	**0.6793**	1.0086	**0.7469**
MIDAS-RET-SP	**0.9269**	**0.8771**	**0.8692**	**0.8983**	**0.9415**	**0.9391**	**0.7184**	**0.7520**	**0.8201**	**0.9033**
MIDAS-RET-XX	**0.8198***	**0.9267**	**0.8140**	1.0237	**0.8463**	**0.7552***	**0.7467**	**0.6577**	1.0603	**0.7227**
MIDAS-RET-HI	**0.8776**	**0.8737**	**0.8663**	**0.9931**	**0.8609**	**0.8233**	**0.6857**	**0.7239**	1.0045	**0.7626**
MIDAS-RET-BP	**0.9120**	**0.8756**	**0.9321**	**0.9525**	**0.7956**	**0.8821**	**0.6983**	**0.8591**	**0.9445**	**0.6426**
MIDAS-RET-CD	**0.9301**	**0.9068**	**0.8265**	**0.9031**	**0.8504**	**0.8518**	**0.7507**	**0.6437**	**0.8308**	**0.7307**
MIDAS-RET-EC	**0.9214**	**0.9464**	**0.8689**	**0.8372**	**0.7697**	**0.8489**	**0.8438**	**0.7406**	**0.7064**	**0.5973**
MIDAS-RET-GC	**0.8697***	**0.9821**	**0.7784**	1.0612	1.0692	**0.8018**	**0.8831**	**0.6112**	1.1465	1.1627
MIDAS-RET-HG	**0.9091**	**0.9004**	**0.7768**	**0.8652**	**0.9503**	**0.9054**	**0.7398**	**0.5873**	**0.7761**	**0.9018**
MIDAS-RET-NG	**0.8504***	**0.9911**	**0.7763**	1.0247	**0.8975**	**0.7665***	**0.8738**	**0.6102**	1.0668	**0.8182**
MIDAS-RET-PA	**0.9072**	**0.8550**	**0.8160**	**0.8780**	**0.9300**	**0.8753**	**0.6768**	**0.6637**	**0.7898**	**0.8782**
MIDAS-RET-SV	**0.8688***	**0.9029**	**0.7783**	**0.7332**	**0.8832**	**0.7963**	**0.8020**	**0.5912**	**0.5455**	**0.8025**
MIDAS-RET-TY	**0.8532***	**0.9308**	**0.8587**	**0.9684**	**0.7828**	**0.7975**	**0.8596**	**0.7127**	**0.9561**	**0.6252**

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test.

Table 8: Success ratios during the oil collapse period. Evaluation period: 2014.6-2015.8.

	Success ratio				
Model:	1-month	3-months	6-months	9-months	12-months
AR(1)	**0.5385**	0.2143	0.3077	0.1538	0.1538
ARMA(1,1)	**0.5385**	0.2143	0.3077	0.1538	0.1538
AR(12)	0.1538	0.3571	0.3077	0.1538	0.1538
AR(24)	0.1538	0.2857	0.3077	0.1538	0.1538
3-VAR(12)	0.3846	0.2143	**0.5385**	0.4615	0.1538
3-VAR(24)	0.1538	0.2143	0.1538	0.1538	0.1538
4-VAR(12)	0.3846	0.2143	**0.5385**	0.3846	0.1538
4-VAR(24)	0.1538	0.2143	0.1538	0.1538	0.1538
3-BVAR(12)	0.3846	0.4286	**0.5385**	0.4615	0.4615
3-BVAR(24)	0.4615	0.4286	0.4615	0.4615	**0.5385****
4-BVAR(12)	0.4615	0.4286	**0.5385**	0.4615	0.4615
4-BVAR(24)	0.4615	0.4286	0.4615	0.4615	**0.5385****
MIDAS-RV-CO	0.3846	0.3571	0.4615	0.2308	0.1538
MIDAS-RV-FT	0.4615	0.3571	0.4615	0.1538	0.1538
MIDAS-RV-SP	0.4615	0.3571	0.3846	0.1538	0.1538
MIDAS-RV-XX	**0.5385**	0.4286	0.3846	0.2308	0.1538
MIDAS-RV-HI	**0.5385**	0.3571	0.4615	0.2308	0.1538
MIDAS-RV-BP	0.4615	0.3571	**0.6154****	0.2308	0.2308
MIDAS-RV-CD	**0.7692***	0.3571	0.5385	0.1538	0.1538
MIDAS-RV-EC	**0.6923****	0.3571	**0.6154****	0.2308	0.2308
MIDAS-RV-GC	**0.5385**	0.3571	0.4615	0.1538	0.2308
MIDAS-RV-HG	**0.6923****	0.3571	**0.5385**	0.1538	0.2308
MIDAS-RV-NG	**0.5385**	0.3571	**0.5385**	0.3077	0.1538
MIDAS-RV-PA	**0.6923****	0.3571	0.3077	0.2308	0.3846
MIDAS-RV-SV	**0.5385**	0.3571	0.4615	0.1538	0.2308
MIDAS-RV-TY	**0.5385**	0.3571	0.3846	0.2308	0.1538
MIDAS-RV-EPU	**0.5385**	**0.5714****	**0.5385**	0.1538	0.1538
MIDAS-RET-CO	0.4615	0.2857	0.3077	0.2308	0.1538
MIDAS-RET-FT	**0.5385**	0.3571	0.4615	0.1538	0.1538
MIDAS-RET-SP	**0.5385**	0.5000	0.4615	0.1538	0.1538
MIDAS-RET-XX	**0.5385**	0.3571	0.3846	0.1538	0.1538
MIDAS-RET-HI	**0.5385**	0.4286	0.3077	0.1538	0.2308
MIDAS-RET-BP	**0.5385**	0.3571	0.3077	0.1538	0.1538
MIDAS-RET-CD	0.4615	0.3571	0.4615	0.2308	0.1538
MIDAS-RET-EC	0.4615	0.3571	0.3846	0.1538	0.1538
MIDAS-RET-GC	**0.6154**	0.3571	0.3846	0.1538	0.1538
MIDAS-RET-HG	**0.5385**	0.3571	0.3846	0.2308	0.1538
MIDAS-RET-NG	**0.6154**	0.3571	**0.6154***	0.1538	0.1538
MIDAS-RET-PA	0.4615	0.3571	0.4615	0.1538	0.1538
MIDAS-RET-SV	**0.5385**	0.3571	0.4615	0.1538	0.2308
MIDAS-RET-TY	**0.5385**	0.4286	0.3077	0.1538	0.2308

Note: The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively. Bold face denotes improvement relatively to the no-change forecast.

Table 9: Forecasting monthly oil prices – MIDAS-RV and MIDAS-RET models based on PCA. Evaluation period: 2011.12-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
Asset volatilities										
MIDAS-RV-Stocks	**0.9019**	**0.9838**	**0.8850**	1.2023	1.0245	**0.8870**	**0.9800**	**0.8126**	1.6851	1.1628
MIDAS-RV-Forex	**0.8933***	**0.8308***	**0.8025**	**0.9195**	**0.8725**	**0.9430**	**0.6981***	**0.6949**	**0.8685**	**0.8323**
MIDAS-RV-Commodities	**0.9882**	1.0569	**0.9296**	1.0305	**0.7984**	1.0535	1.1653	**0.8909**	1.1750	**0.7102**
MIDAS-RV-Macro	1.0008	**0.9710**	1.1893	1.6623	**0.8926**	1.0434	**0.9476**	1.4539	3.2236	**0.8897**
MIDAS-RV-Combined	1.0124	**0.9682**	**0.8642**	1.1662	1.0264	1.1074	**0.8954**	**0.7451**	1.5273	1.1943
Asset Returns										
MIDAS-RET-Stocks	1.1426	**0.9908**	1.2565	1.9910	**0.7456**	1.1930	**0.9823**	1.6626	4.8951	**0.6620**
MIDAS-RET-Forex	1.0280	**0.9470**	1.0365	2.0187	1.1739	1.1019	1.0921	1.1087	4.6586	1.7703
MIDAS-RET-Commodities	1.0321	1.1226	1.3112	1.0867	1.4684	1.0703	1.3262	2.2308	1.3348	2.1872
MIDAS-RET-Macro	**0.9723**	1.0370	1.3589	2.6200	1.7797	**0.9580**	**0.9348**	2.0311	8.3700	3.8064
MIDAS-RET-Combined	1.0623	**0.9771**	1.2775	1.5718	1.5068	1.1837	**0.9796**	2.1063	3.0625	2.7465

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models, according to the Model Confidence Set (MCS) test, along with the best models from Tables 3 & 5.

Table 10: Forecasting monthly oil prices during the oil collapse period – MIDAS-RV and MIDAS-RET models based on PCA. Evaluation period: 2011.12-2015.8.

	MAPPE					MSPE				
	Forecasting horizon					Forecasting horizon				
Model:	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
	Asset volatilities									
MIDAS-RV-Stocks	**0.8224***	**0.9533**	**0.7992**	1.0162	1.0248	**0.8000**	**0.8077**	**0.6338**	1.0443	1.0635
MIDAS-RV-Forex	**0.8234***	**0.7986***	**0.7036**	**0.8652**	**0.7966**	**0.8087**	**0.5736***	**0.4924**	**0.7638**	**0.6386**
MIDAS-RV-Commodities	**0.8857**	**0.9782**	**0.7378**	1.0114	**0.7289**	**0.8587**	**0.8438**	**0.5389**	1.0625	**0.5462**
MIDAS-RV-Macro	**0.9445**	**0.8625**	**0.8635**	1.1601	**0.9450**	**0.9413**	**0.6795**	**0.7255**	1.3427	**0.9261**
MIDAS-RV-Combined	**0.9108**	**0.8952**	**0.7790**	**0.9596**	**0.8600**	**0.9492**	**0.6841**	**0.5798**	**0.9693**	**0.7419**
	Asset Returns									
MIDAS-RET-Stocks	**0.9293**	**0.9025**	**0.8526**	1.0328	**0.8715**	**0.9503**	**0.7251**	**0.7118**	1.0879	**0.7676**
MIDAS-RET-Forex	**0.9116**	**0.9322**	**0.8663**	**0.9098**	**0.9527**	**0.8004**	**0.8297**	**0.7607**	**0.8574**	**0.9317**
MIDAS-RET-Commodities	**0.8947**	**0.9491**	**0.7809**	**0.8062**	**0.9433**	**0.8509**	**0.8337**	**0.6016**	**0.6570**	**0.9104**
MIDAS-RET-Macro	**0.8532***	**0.9308**	**0.8587**	**0.9684**	**0.7828**	**0.7975**	**0.8596**	**0.7127**	**0.9561**	**0.6252**
MIDAS-RET-Combined	**0.9037**	**0.8824**	**0.7827**	**0.8429**	**0.9443**	**0.8801**	**0.7297**	**0.6069**	**0.7533**	**0.9013**

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models, along with these in Table 7, according to the Model Confidence Set (MCS) test.

Table 11: Success ratios of the MIDAS-RV and MIDAS-RET models based on PCA. Evaluation period: 2011.12-2015.8.

	Success ratio during the full out-of-sample period				
Model:	1-month	3-months	6-months	9-months	12-months
	Asset volatilities				
MIDAS-RV-Stocks	**0.5349**	**0.5122**	**0.5263**	0.4000	0.3125
MIDAS-RV-Forex	**0.6047***	**0.5122**	**0.5789***	0.4286	0.2188
MIDAS-RV-Commodities	0.4884	0.4878	0.4737	**0.5143**	0.3125
MIDAS-RV-Macro	0.4419	0.5122	0.4737	0.3429	0.3125
MIDAS-RV-Combined	0.4884	0.5122	0.4737	0.4000	0.3125
	Asset returns				
MIDAS-RET-Stocks	0.4186	**0.5610**	0.5000	0.4571	0.2500
MIDAS-RET-Forex	0.4651	**0.6098**	0.4474	0.4286	0.2813
MIDAS-RET-Commodities	0.4651	0.4634	0.5000	**0.5143**	0.2813
MIDAS-RET-Macro	0.4884	**0.5610**	0.5000	0.3143	0.3125
MIDAS-RET-Combined	**0.5116**	**0.5366**	0.4737	0.4286	0.2813
	Success ratio during the oil collapse period				
Model:	1-month	3-months	6-months	9-months	12-months
	Asset volatilities				
MIDAS-RV-Stocks	**0.5385**	0.3571	0.4615	0.1538	0.1538
MIDAS-RV-Forex	**0.6154**	0.3571	**0.6154****	0.1538	0.1538
MIDAS-RV-Commodities	**0.6154**	0.3571	**0.5385**	0.1538	0.2308
MIDAS-RV-Macro	0.4615	0.4286	0.3846	0.1538	0.1538
MIDAS-RV-Combined	**0.6154**	0.4286	0.4615	0.2308	0.1538
	Asset returns				
MIDAS-RET-Stocks	**0.5385**	**0.5714***	**0.5385**	0.1538	0.1538
MIDAS-RET-Forex	0.4615	0.3571	0.4615	0.1538	0.1538
MIDAS-RET-Commodities	**0.5385**	0.2857	0.4615	0.1538	0.2308
MIDAS-RET-Macro	**0.5385**	0.4286	0.3077	0.1538	0.2308
MIDAS-RET-Combined	0.4615	0.4286	0.4615	0.2308	0.1538

Note: The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively. Bold face denotes improvement relatively to the no-change forecast.

Table 12: Forecasting monthly oil prices - forecast combinations.

	MAPPE					MSPE				
	1-month	3-months	6-months	9-months	12-months	1-month	3-months	6-months	9-months	12-months
Model:	Full out-of-sample period									
FC-Benchmarks	1.4151	1.0052	**0.8013**	**0.6709***	**0.5866**	1.9760	**0.9832**	**0.7363**	**0.5558***	**0.4287**
FC-MIDAS-RV	**0.9160**	**0.9285**	**0.8951**	1.0633	**0.8825**	**0.9183**	**0.9063**	**0.8547**	1.2883	**0.8408**
FC-MIDAS-RET	**0.9132**	**0.9141**	**0.9050**	1.0265	**0.8958**	**0.8786**	**0.8943**	**0.8496**	1.1341	**0.8547**
FC-All	1.0485	**0.8701**	**0.7901**	**0.8631**	**0.7314**	1.0318	**0.8127**	**0.7109**	**0.8405**	**0.6025**
	Oil collapse period									
FC-Benchmarks	1.4416	1.0914	**0.8714**	**0.7608**	**0.7117**	2.0312	1.0177	**0.7498**	**0.6071**	**0.5207**
FC-MIDAS-RV	**0.8743**	**0.9177**	**0.7878**	**0.9616**	**0.8923**	**0.8425**	**0.7423**	**0.6179**	**0.9442**	**0.7998**
FC-MIDAS-RET	**0.8901**	**0.9236**	**0.8275**	**0.9278**	**0.8789**	**0.8339**	**0.7701**	**0.6721**	**0.8697**	**0.7785**
FC-All	1.1034	**0.8800**	**0.7731**	**0.8722**	**0.8121**	1.0811	**0.7714**	**0.6496**	**0.7819**	**0.6647**

Note: All MAPPE and MSPE ratios have been normalized relative to the monthly no-change forecast. FC stands for Forecast Combination. Bold face indicates predictive gains relatively to the no-change forecast. * denotes that the model is among the set of the best performing models according to the Model Confidence Set (MCS) test, along with the best models from Tables 3, 4 and 7.

Table 13: Success ratios of the forecast combinations.

	Success ratio				
:	1-month	3-months	6-months	9-months	12-months
Model:	Full out-of-sample period				
FC-Benchmarks	0.4419	0.4390	**0.5263**	**0.5714**	0.4375
FC-MIDAS-RV	**0.5814**	**0.5122**	0.5000	0.4571	0.2188
FC-MIDAS-RET	0.4884	**0.5366**	**0.5263**	0.4000	0.2188
FC-All	0.4884	0.4390	0.5000	**0.5143**	0.2813
	Oil collapse period				
FC-Benchmarks	0.3077	0.2143	0.3077	0.2308	0.2308
FC-MIDAS-RV	**0.6154**	0.3571	0.4615	0.1538	0.1538
FC-MIDAS-RET	0.4615	0.3571	0.3846	0.1538	0.1538
FC-All	0.2308	0.2857	0.3846	0.2308	0.1538

Note: FC stands for Forecast Combination. The statistical significance of the success ratios is tested based on the Pesaran and Timmermann (2009) under the null hypothesis of no directional accuracy. ** and * denote significance at 5% and 10% level, respectively. Bold face denotes improvement relatively to the no-change forecast.